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"Category Learning by Clustering with Extension to Dynamic Environments"

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14. ABSTRACT
This project focuses on how humans master new categories by learning from examples with extension to dynamic environments. Decision making tends to take place in dynamic environments in which successive decisions are contingent on one another, and in which the rewards associated with actions can be delayed, yet most tasks that have been studied in the laboratory are broken up into brief, independent trials (e.g., classification of a stimulus) in which responses are determined only by the immediate context and have no bearing on future states of the task environment. Thus, this project narrows the gap between the range of mental processes typically addressed by cognitive scientists and the mental processes that underlie performance in Air Force relevant activities. We find that people's performance profiles are generally consistent with modern reinforcement learning models.

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Abstract

This project focuses on how humans master new categories by learning from examples with extension to dynamic environments. Decision making tends to take place in dynamic environments in which successive decisions are contingent on one another, and in which the rewards associated with actions can be delayed, yet most tasks that have been studied in the laboratory are broken up into brief, independent trials (e.g., classification of a stimulus) in which responses are determined only by the immediate context and have no bearing on future states of the task environment. Thus, this project narrows the gap between the range of mental processes typically addressed by cognitive scientists and the mental processes that underlie performance in Air Force relevant activities. We find that people's performance profiles are generally consistent with modern reinforcement learning models. For example, including perceptual information that disambiguates a person's current state within a task improves performance. Additionally, consistent with model-based predictions, people appear to hill climb on reward gradient, as opposed to globally optimize performance, and show other suboptimal behavior, such as poorer performance under certain circumstance when given more information about response options.

Project Overview

In this project, the PI and his collaborators have made progress in understanding human category learning and have extended this work to dynamic decision making environments. Below, findings from this project are briefly reviewed. Following this review, doctoral students who have graduated during this project are listed, as our project publications.

Todd Gureckis and the PI have published a number of articles that develop the sequential learning aspects of the project. In the Cognitive Science article, we conduct a formal model comparison of simple recurrent and buffer networks and find that the simpler buffer networks do a better job of characterizing human learning and sequential performance. Surprisingly, there has been little previous fine grain evaluation of sequential learning models. We derived predictions from our buffer network and found a strong linear (through time) constraint on human sequential learning that is not present in human category learning.

In two papers, one published in the Journal of Mathematical Psychology and the other in Cognition, we explore human learning and decision making in a dynamic environment in which short- and long-term rewards are put in conflict. We find that people can learn to make long-term responses when state cues are present that de-alias underlying system states and allow for generalization of rewards to yet unexplored states. In noisy environments, we find that noise on state cues is much more detrimental to human and model performance than is equivalent noise on rewards, even though rewards define the learning problem. In fact, moderate levels of noise on rewards can be beneficial in that it encourages exploration in a task in which humans and models under explore.

We use simple reinforcement learning models to derive our study designs and characterize our results.

Three other papers have been published exploring human learning and decision making when short- and long-term rewards are in conflict. In a paper published in Psychonomic Bulletin & Review, we examined whether state cues make people more rational or just more sensitive to the gradient of reward as our models predict. By comparing performance when reward curves are close or far apart, we found that state cues led people to be more sensitive to reward gradient, not more rational. People hill climbed toward states with increasing rewards even when doing so was not optimal. In a Judgment and Decision Making paper, we found (as reinforcement learning models predict) that giving additional information about forgone rewards (i.e., information about the choice option not selected) lowers performance (i.e., people meliorate and choose the short-term option). Finally, in a Journal of Experimental Psychology: Learning, Memory, & Cognition paper, we manipulate people's motivational focus and find a systematic effect on people's exploration strategies. In particular, people are more streaky (i.e., explore systematically by making a number of identical responses consecutively) when in a regulatory fit motivational state.

In two papers (a Memory & Cognition and Psychological Science paper), we find that people’s estimation of category mean and variance is consistent with error-driven learning models that make sequential updates. In the Psychological Science paper, we find that people’s conceptions of categories distort away from contrasting categories. The mechanisms we explore in these papers can explain high-level idealization effects.

Finally, in a second Memory & Cognition paper, we find evidence for two pathways for stimulus encoding. We borrow theoretical ideas from the object recognition literature. We find that one pathway that experts use is holistic and whereas the second pathway is more part-based or discrete. This latter pathway requires effortful processing to decompose and analyze stimulus parts. Although many researchers have explored the possibility that there are multiple learning systems in the brain, fewer have explored the possibility that visual stimuli can be encoded in multiple formats.

A final journal article most closely related to the proposed work is the Maddox et al. contribution. In that paper, rule-based and information-integration category learning were compared under minimal and full feedback conditions. Rule-based category structures are those for which the optimal rule is verbalizable. Information-integration category structures are those for which the optimal rule is not verbalizable. With minimal feedback subjects are told whether their response was correct or incorrect, but are not informed of the correct category assignment. With full feedback subjects are informed of the correctness of their response and are also informed of the correct category assignment. An examination of the distinct neural circuits that subserve rule-based and information-integration category learning leads to the counterintuitive prediction that full feedback should facilitate rule-based learning but should also hinder information integration learning. These predictions held. The results were

modeled by a reinforcement learning system and a Bayesian hypothesis testing system whose outputs were combined by a gating mechanism. The reinforcement learning systems processing of only feedback valence was explained by making recourse to additional dynamic tasks it subserves, like motor control and the kinds of problems considered in the aforementioned Gureckis and Love papers.

Dissertations Supported By Grant

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Marc T. Tomlinson (2010). Building BRIDGES: Combining analogy and category learning to learn relation-based categories. University of Texas at Austin.

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